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Research Article

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Optimal design of the rotor geometry of line-start permanent magnet synchronous motor using the bat algorithm

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Abstract: In this paper an algorithm for the optimization of excitation system of line-start permanent magnet synchronous motors will be presented. For the basis of this algorithm, software was developed in the Borland Delphi environment. The software consists of two independent modules: an optimization solver, and a module including the mathematical model of a synchronous motor with a self-start ability. The optimization module contains the bat algorithm procedure. The mathematical model of the motor has been developed in an Ansys Maxwell environment. In order to determine the functional parameters of the motor, additional scripts in Visual Basic language were developed. Selected results of the optimization calculation are presented and compared with results for the particle swarm optimization algorithm.

Keywords: bat algorithm; line-start permanent magnet motor; constrained optimization

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1 Introduction

The motivation to analyze and synthesize new structures of machines excited by permanent magnets has been driven by the development of the material technology. The manufacturers have produced permanent magnets allowing for a high density of energy and improved parameters concerning magnetic, thermal and mechanical properties. Therefore, for the last couple of years it has been possible to observe a dynamic development of new constructions of permanent magnet machines. The variety of magnetic properties of permanent magnets influences the diversity of construction of permanent magnet motors.

In the last period years, an interesting alternative for the permanent magnet synchronous motor (PMSM) has appeared in a form of motors with self-starting ability: line-start permanent magnet motors (LSPMSM). An increase in interest in these machines was recorded by multiple research teams throughout the world [1–4]. The basic advantage of LSPMSM is a possibility of direct start-up after connecting to a three-phase grid.

Designers and constructors of the machines use powder technology more and more often. This concerns both soft and hard magnetic material. In the most innovative projects, magnetic circuits have been used which have been built of both soft and hard magnetic material. Also, hybrid structures, *i.e.* the structures with excitation systems composed of two or more materials with different magnetic properties have been used [5].

Further development of new constructions of permanent magnet motors depends on improving the methods of simulations, as well as their design and optimization.

The designing process itself is often supported by computations. With the use of a computational environment consisting of a numerical model of a motor combined with an efficient optimizing procedure, it is possible to find solutions for the synthesis of the machines excited by permanents magnets.

The modern design process most frequently uses discrete field-circuit models of electromagnetic phenomena in the considered device [6, 7]. Such models are computationally sophisticated, optimization processes using them are very time consuming. For that reason, new optimization algorithms have been developed, which are particularly effective for solving tasks concerning the synthesis of permanent magnet machines. Many different non-deterministic optimization algorithms are popular, such as: particle swarm optimization (PSO), genetic algorithms (GA), brain storm optimization (BSO) method, ant colony optimization (ACO) and cuckoo search (CS) [8–12]. Re-

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search is still being conducted with an aim to develop new, even more effective optimization methods.

The aim of this paper is to recognize the areas of application for a bat algorithm to solve the optimization tasks for the machines with permanent magnets.

2 The bat algorithm

The bat algorithm (BA) is inspired by the echolocation behaviour of a small species of bats. Echolocation helps bats orient themselves in the dark for hunting. Most bats using echolocation emit ultrasonic waves of frequency varying from 20 kHz to 100 kHz.

The BA was introduced in 2010 [13]. This algorithm combines the advantages of two different non-deterministic optimization methods: the particle swarm optimization (PSO) and the simulated annealing (SA). The SA method shows high probability of finding a global optimum but only provided that the optimization process is carried out slowly enough. Nowadays, this method is rarely used as a tool to solve tasks of synthesis of permanent magnet machines. On the other hand, the PSO method is commonly used for such tasks [9, 14]. In its classic form, one can notice a strong correlation between the placement of the swarm leader and the trajectory of the whole swarm, where the swarm leader is the most adjusted particle in the swarm system. For this reason, the most advanced method of PSO includes some modifications for the improvement of the performance and the quality of calculations.

The set of bats constitute the colony. Each individual bat represents an acceptance solution of the optimization task. Each bat is described by position $\mathbf{x}^i$ and velocity $\mathbf{v}^i$. Moreover, it is characterized by variable frequency F^i, loudness A^i and the rate of pulse emission r^i. In j-th time step, the bats know the position of leader $\mathbf{x_B}$ – the best bat in the colony. In order to calculate position vector for i-th individual, the following formula is used:

$$\mathbf{x}_j^i = \mathbf{x}_{j-1}^i + \left[\mathbf{v}_{j-1}^i + F^i \cdot \left(\mathbf{x}_{j-1}^i - \mathbf{x}_B\right)\right] \tag{1}$$

where $F^i = F_{\min} + r_1(F_{\max} - F_{\min})$, $F_{\max}$, $F_{\min}$ are the minimum and maximum value of frequency, r_1 is the random number, usually selected from the range (0, 1).

The method of setting new consecutive velocity vectors and bats' position vectors is similar to the algorithm used in the PSO method. The dynamics of bats' movements in a space of a considered problem depends on the range of change of frequency.

In order to imitate precisely the tactic of a single bat's hunting, there are two additional parameters defined in the algorithm: a loudness parameter A^i and the rate of pulse emission r^i. A hunting bat emits on average 5 – 10 impulses per second but this depends on the species. If it locates an insect in the surroundings, at this very moment the quantity of the impulses raises up to as many as 50 impulses per second. And it is the coefficient r^i that shows the dynamics of the change of impulses emitted by a bat. This proved to be the most successful parameter order to obtain an improved value of the objective function in the optimization calculations.

The block diagram of the bat algorithm is presented in Figure 1.

After setting new positions of each and every bat in the j-th time step, a value of β_1 is randomly picked from the range (0, 1), as shown in the Figure 1. Taking into consideration the value of β_1 and the average coefficient of pulse emission for the whole colony r_{av}, a new position is defined for the current best-bat in the colony or for a randomly chosen bat according to the formula:

$$(\mathbf{x}^{\star})_j^i = \mathbf{x}_j^i + \chi A_{av} \tag{2}$$

where χ is the random number from range (-1, 1), A_{av} is the average loudness of all bat population in the j-th time step.

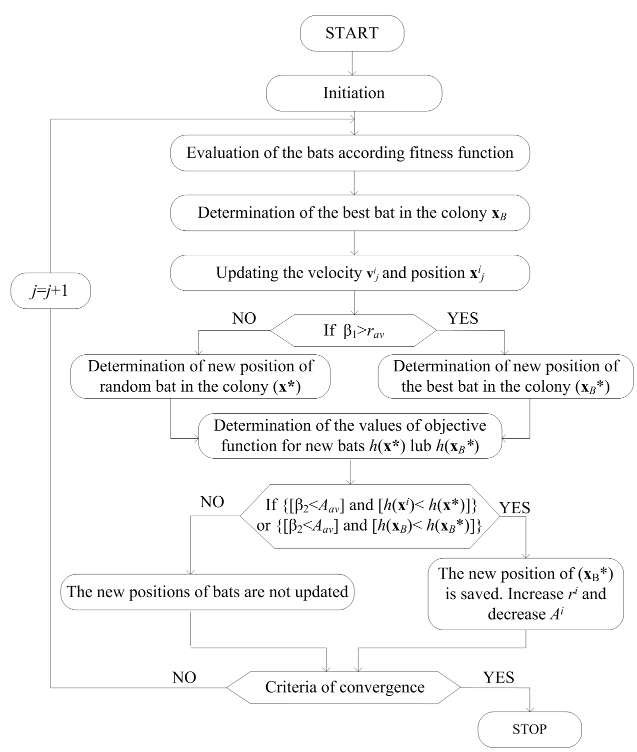

Figure 1: Flowchart of the bat algorithm

If a bat attains a better value of the objective function and it gets closer to the searched optimum point and the random parameter β_2 from the range (0, 1) is smaller than the average loudness A_{av} of the whole colony, then the rate of pulse emission r^i is increased and the loudness A^i is decreased:

$$A_{j+1}^i = \alpha A_j^i \quad r_{j+1}^i = r_0 \left[1 - \exp(-\gamma j)\right] \tag{3}$$

where α and γ are the constants, and r_0 is the initial value of emission rate.

3 The optimization procedure

In order to analyze the efficiency of the bat algorithm, the optimization of the rotor geometry of LSPMSM is executed. The structure of considered LSPMSM is presented in Figure 2.

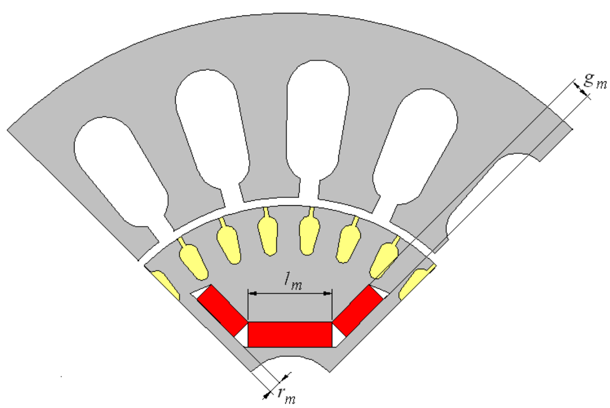

Figure 2: The LSPMSM structure

The task of the optimization was defined as follows: for known parameters such as stator and squirrel-cage structural parameters, air gap length and stack length, the structural parameters describing the excitation system (g_m, r_m and l_m – see Figure 2) had to be found in such a way that these parameters would assure the maximum value of the product of an efficiency η and a power factor $\cos\varphi$. The exciting system was described with the use of three design variables: $s_1 = l_m$ –permanent magnet width, $s_2 = g_m$ – the thickness of the magnet and $s_3 = r_m$ –distance between the poles. All design variables s_j in the optimization process have been transformed into dimensionless quantities x_j using the following formula [15]:

$$x_j = \frac{s_j - s_{\min j}}{s_{\max j} - s_{\min j}} \tag{4}$$

where $s_{\min j}$ and $s_{\max j}$ are the expected lower and upper limits of each variable s_j, respectively.

These parameters x_j form a normalized vector $\mathbf{x}$.

The objective function for i-th bat has been defined as follows:

$$f^i(\mathbf{x}) = \left(\frac{\eta^i(\mathbf{x})}{\eta_0}\right)\left(\frac{\cos\varphi^i(\mathbf{x})}{\cos\varphi_0(\mathbf{x})}\right) \tag{5}$$

here: $\eta^i(\mathbf{x})$, $\cos\varphi^i(\mathbf{x})$ are the efficiency and power factor for i-th bat, η_0, $\cos\varphi_0$ are the average values of efficiency and power factor after the initiation procedure.

In the optimization process, a function (5) was maximized, while the non-linear constrains regarding the permissible values of the total mass of permanent-magnet material $m_m \le m_z$ and the electromagnetic torque $T_{80}(\mathbf{x}) \ge T_z$, where T_{80} is the synchronizing torque produced by the motor at 0.8 of the synchronous speed. The high value of torque enables proper synchronization during starting. The constraint functions have been normalized and are describedas follows:

$$g_1(\mathbf{x}) = \left(1 - T_{80}(\mathbf{x})/T_z\right) \le 0 \tag{6}$$

In the described algorithm, the constraints were included with the use of an external penalty function. According to this method, the modified objective function $h_k(\mathbf{x})$ is created. The value of the penalty component $p_k(\mathbf{x})$ increases in successive time steps of the bat algorithm. The subsequent superior iterations depend on the assumed constraints, the $p_k(\mathbf{x})$ component was calculated as follows:

$$p_k(\mathbf{x}) = a^k\left(\lambda_1 g_1(\mathbf{x}) + \lambda_2 g_2(\mathbf{x})\right) \tag{7}$$

where a^k is the penalty coefficient, a is the real number greater than 1, k is the number of penalty iterations.

In case the objective function $f(\mathbf{x})$ is maximised, the modified function i-th bat has a form [16, 17]:

$$h^i(\mathbf{x}) = \begin{cases} f^i(\mathbf{x}) & \text{for } (T_{80}(\mathbf{x}) > T_z) \wedge (m_m(\mathbf{x}) < m_z) \\ f^i(\mathbf{x}) - p_k(\mathbf{x}) & \text{for } (T_{80}(\mathbf{x}) < T_z) \vee (m_m(\mathbf{x}) > m_z) \end{cases} \tag{8}$$

It should be noted that in order to calculate the efficiency and power factor of the motor, additional scripts which cooperate with a Maxwell environment have been developed. The efficiency was calculated on the basis of electrical and mechanical discrete values. The value of the power factor is computed from the real and apparent power. The real power is determined as an integral from values of voltages and currents in the period of the supply voltage.

Table 1: The comparision of optimization results

j	r_m [mm]	g_m [mm]	l_m [mm]	$\eta(\mathbf{x}_B)$ [%]	$\cos\varphi(\mathbf{x}_B)$ [–]	$T_{80}(\mathbf{x}_B)$ [Nm]	$m_m(\mathbf{x}_B)$ [kg]	$h(\mathbf{x}_B)$ [-]	h_{av} [-]
0	1.74	3.70	14.21	94.49	0.835	30.59	0.158	1.06736	0.1962
1	5.57	4.46	16.10	95.02	0.897	28.48	0.245	1.15304	0.2519
2	7.76	5.95	19.12	95.27	0.974	21.72	0.469	1.25598	0.4563
4	7.46	6.20	20.02	95.24	0.981	20.67	0.471	1.26388	0.2035
7	7.47	6.20	20.02	95.23	0.982	20.26	0.482	1.26546	0.4313
12	4.89	6.11	21.75	95.12	0.988	20.59	0.488	1.27164	0.6774
17	4.89	6.11	21.75	95.12	0.988	20.59	0.468	1.27164	0.2760
20	8.98	5.73	21.73	95.12	0.987	21.01	0.468	1.27056	0.7060
25	10.87	4.70	25.30	94.82	0.996	22.13	0.491	1.27759	0.3893
30	10.37	4.65	26.01	94.75	0.997	22.06	0.499	1.27849	0.3301
40	10.89	4.90	25.95	94.74	0.999	20.11	0.499	1.27999	0.8119
60	10.89	4.90	25.95	94.74	0.999	20.09	0.499	1.27999	0.8556

Table 2: Statistical data for BA in 15 optimization processes

	r_m	g_m	l_m	$\eta(\mathbf{x}_B)$	$\cos\varphi(\mathbf{x}_B)$	$m_m(\mathbf{x}_B)$
Best	10.841	4.903	25.953	94.739	0.999	0.500
Worst	10.687	5.176	25.427	94.807	0.998	0.497
Mean	10.789	5.017	26.192	94.741	0.9989	0.499
Standard deviation	0.4808	0.101	1.5868	0.0466	0.0004	0.009

4 Results of optimization

In order to validate the developed computer software, a large number of computer simulations have been performed. The optimization process was run 15 times. In each case, the same reference values $\eta_0 = 84\%$ and $\cos\varphi_0 = 0.88$ have been assumed as the average values of several random starts of software. The initial population was also the same for all studied cases. The calculations on a colony with $N = 50$ bats have been performed. The following values of the parameters of the BA algorithm have been assumed: $F_{\min} = 0$, $F_{\max} = 1.2$, $r_0 = 0$, $A_0 = 1$, $\alpha = 0.75$ and $\gamma = 0.5$ [18]. The following parameters of the optimization procedure have been assumed: $\lambda_1 = 0.5$, $\lambda_2 = 0.5$ and $a = 1.2$. In single penalty iteration, the five time-steps of the BA algorithm are executed. The permissible values of: $m_z = 0.5$ kg and $T_z = 20$ Nm have been imposed. The course of the best optimization process after 15 runs of the program is presented in Table 1. In the successive columns, the values of design variables, components of objective function, value of modified objective function for the best individual in a colony and the average value of modified objective function for a colony in the selected time step have been listed.

As presented within the table, the result closest to the optimal result has been obtained after approximately 40 time-steps. During the whole optimization process, determination of a new position, according to (2), was only achieved in four cases. The movement trajectory of bats in successive time steps may be strongly dependent on the BA algorithm parameters.

The statistical data obtained during the test runs of the software are presented in Table 2. The mean values and standard deviations for the design variables and components of the objective function have been determined from 15 runs of the program.

The mean value of the efficiency and power factor is close to the best result. Also the value of standard deviation for those functional parameters is very small. The imposed constraints were fulfilled in all considered cases. Similarly, the standard deviations for imposed constraints also have very small values.

Table 3: Comparison of the parameters for the best individual for BA and PSO algorithms

Algorithm	r_m [mm]	g_m [mm]	l_m [mm]	$\eta(\mathbf{x}_B)$ [%]	$\cos\varphi(\mathbf{x}_B)$ [–]	$m_m(\mathbf{x}_B)$ [Nm]
BA	10.841	4.9035	25.953	94.739	0.9987	0.4999
PSO	10.912	5.0787	26.078	94.740	0.9987	0.4999

5 The bat algorithm versus particle swarm optimization

The results of the optimization process of two non-deterministic optimization algorithms have been compared. The BA and PSO methods have been taken into consideration. Both versions of the software have been equipped with the same mathematical model of the motor. The initial population was the same for both tested algorithms. Also, the parameters of the optimization procedure (λ_1, λ_2 and a), permissible values (m_z and T_z) and reference values (η_0 and $\cos\varphi_0$) were the same.

The control parameters of the PSO procedure were selected on the basis of author's experience [14]. The optimization calculations on a swarm with N = 50 have been executed. Table 3 shows a comparison between BA and PSO algorithms.

As it can be observed, the values of functional parameters and constraints are similar. On the other hand, the values of design variables for the PSO algorithm are close to the mean values obtained from 15 runs of the process with the BA algorithm.

Changes to the modified objective function for the BA and the PSO algorithms have been analyzed. The values of the modified objective function for the best individual in the colony/swarm were considered. The results are shown in Figure 3.

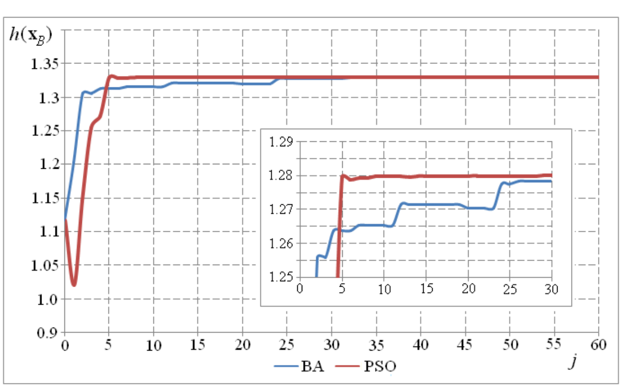

Figure 3: Comparison between BA and PSO algorithms

According to Figure 3, it can be noticed that the classical PSO algorithm ensures faster convergence in comparison to the BA. The PSO achieves the optimal value of objective function even with far fewer numbers of time-steps. However, at the initial stage of optimization, the bat algorithm was much better.

It is interesting to observe the change of value of the total mass of permanent magnet material in the successive time steps j. The values of m_m for the best individuals were analyzed. The results are presented in Figure 4.

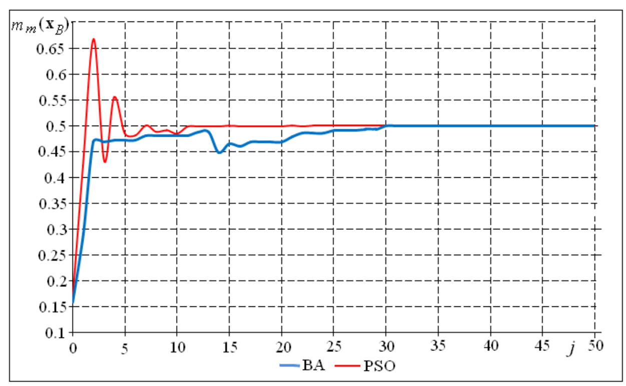

Figure 4: Change of the value of mass of the best individual in swarm/colony for BA and PSO algorithms

For the PSO algorithm the oscillations has been observed during the optimization process. In spite of the rapid changes at the initial stage of the optimization process, the imposed constraint is reached with far fewer time steps in comparison to BA. However, in the case of the BA method, the value of m_m never exceeds the imposed value.

6 Conclusions

This paper presents the application of the bat algorithm for the rotor structure optimization of the line-start permanent magnet synchronous motor. The results of test calculations are encouraging. In the author's opinion the BA algorithm seems to be an interesting method in relation to other well-known non-deterministic optimization methods, in particular PSO and GA. The algorithm may be applied for solving complex designing problems of optimization of permanent-magnet machines.

Throughout the presented results for both optimization algorithms, it was observed that the PSO algorithm allows for better convergence to be achieved in comparison with the BA algorithm. In order to improve the convergence and quality of the solution of the bat algorithm, the modifications of the classical method should be introduced.

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